What Drives the Price of Used Cars

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This document summaries our process and finding and recommendation using a Machine Learning system from scratch including to build predictive model. Here is a high-level process I followed:

- Data cleaning
- Exploratory Data Analysis (EDA)
- Building machine learning models: Linear Regression, Ridge Regression, Lasso, and KNN
- Comparison of the performance of the models
- Summary findings of the study with recommendations and next steps

The Problem

Due to the supply chain issues because of increased consumer demand and inflation the prices of used cars have been on the rise. The higher price and limited supply of new cars and the incapability of customers to buy new cars due to the lack of funds due to the current economic conditions, used cars sales are on the rise globally i. There is a need for a used car price prediction system to effectively determine the worthiness of the car using a variety of features. The dealerships can use these models to plan and optimize their inventory and have a better visibility into a used car’s actual market value.

The Client

To be able to predict used cars market value can help both buyers and sellers.

Used car sellers (dealers): They are one of the biggest target group that can be interested in results of this study. If used car sellers better understand what makes a car desirable, what the important features are for a used car, then they may consider this knowledge and offer a better service.

The Data

The data used in this project was provided by the dealership network for analysis.

```
df=pd.read_csv('/content/drive/MyDrive/practical_application_II_starter (2)/data/vehicles.csv')
```

Let's take a look at the csv

```
df.head(10).transpose()
```

	0	1	2	3	4	5	6	7	8	9
id	7222695916	7218891961	7221797935	7222270760	7210384030	7222379453	7221952215	7220195662	7209064557	7219485069
region	prescott	fayetteville	florida keys	worcester / central MA	greensboro	hudson valley	hudson valley	hudson valley	medford-ashland	erie
price	6000	11900	21000	1500	4900	1600	1000	15995	5000	3000
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
manufacturer	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
condition	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
cylinders	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
fuel	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
odometer	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
title_status	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
transmission	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
VIN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
drive	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
size	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
type	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
paint_color	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
state	az	ar	fl	ma	nc	ny	ny	ny	or	pa

Caption

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 426880 entries, 0 to 426879
Data columns (total 18 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   id            426880 non-null  int64
 1   region        426880 non-null  object
 2   price         426880 non-null  int64
 3   year          425675 non-null  float64
 4   manufacturer  409234 non-null  object
 5   model         421603 non-null  object
 6   condition     252776 non-null  object
 7   cylinders     249202 non-null  object
 8   fuel          423867 non-null  object
 9   odometer      422480 non-null  float64
 10  title_status  418638 non-null  object
 11  transmission  424324 non-null  object
 12  VIN           265838 non-null  object
 13  drive         296313 non-null  object
 14  size          120519 non-null  object
 15  type          334022 non-null  object
 16  paint_color   296677 non-null  object
 17  state         426880 non-null  object
dtypes: float64(2), int64(2), object(14)
memory usage: 58.6+ MB
```

Caption

Data cleaning: First step for data cleaning was to remove unnecessary features. As a next step, it was

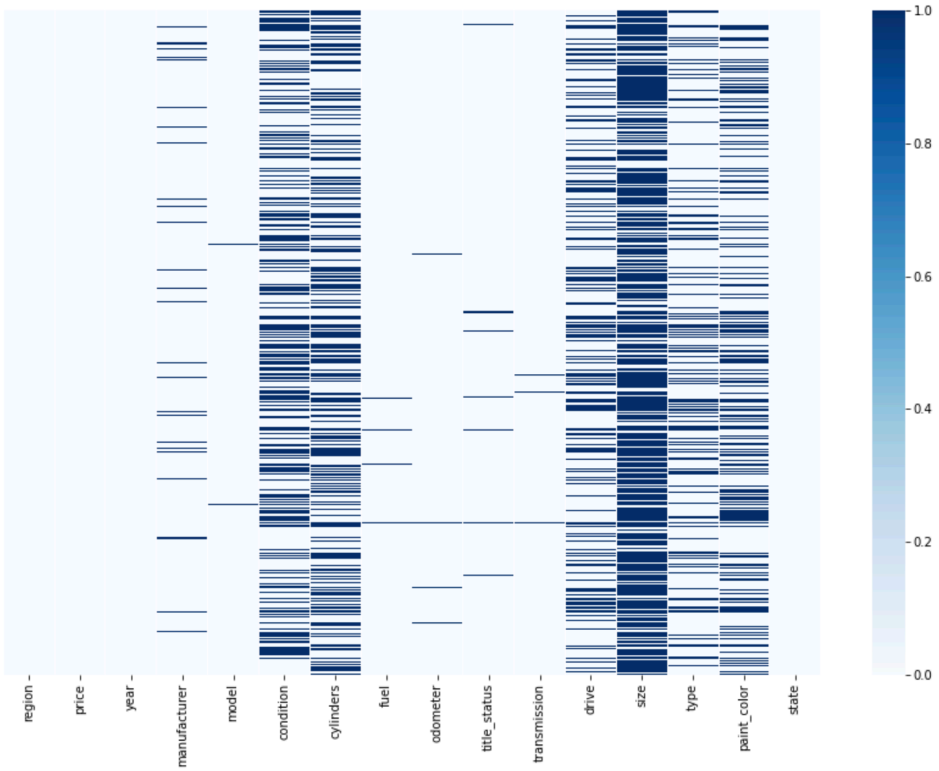
[ ]:

	null	percent
size	30636100	71.767
cylinders	17767800	41.622
condition	17410400	40.785
drive	13056700	30.586
paint_color	13020300	30.501
type	9285800	21.753
manufacturer	1764600	4.134
title_status	824200	1.931
model	527700	1.236
odometer	440000	1.031
fuel	301300	0.706
transmission	255600	0.599
year	120500	0.282
region	0	0.000
price	0	0.000
state	0	0.000

Caption

investigated number of null points and percentage of null data points for that feature.

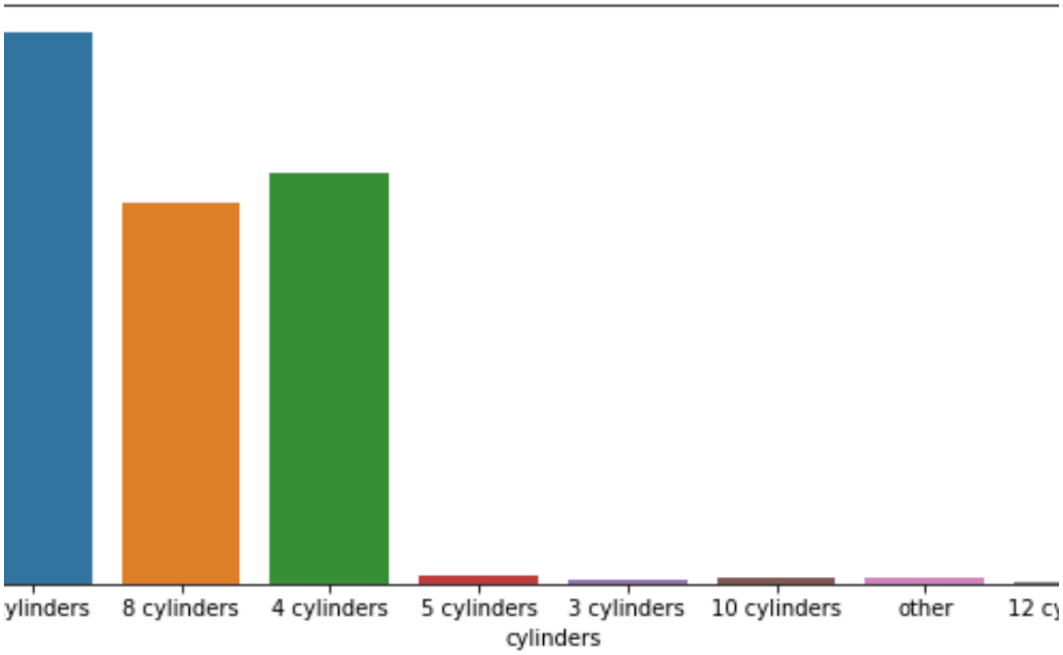
```
plt.figure(figsize=(15,10))
sns.heatmap(df1.isna(),yticklabels=False,cbar=True, cmap='Blues')
#sns.heatmap(df2.isna(), yticklabels=False, cbar=True, cmap='Accent')
plt.show()
```



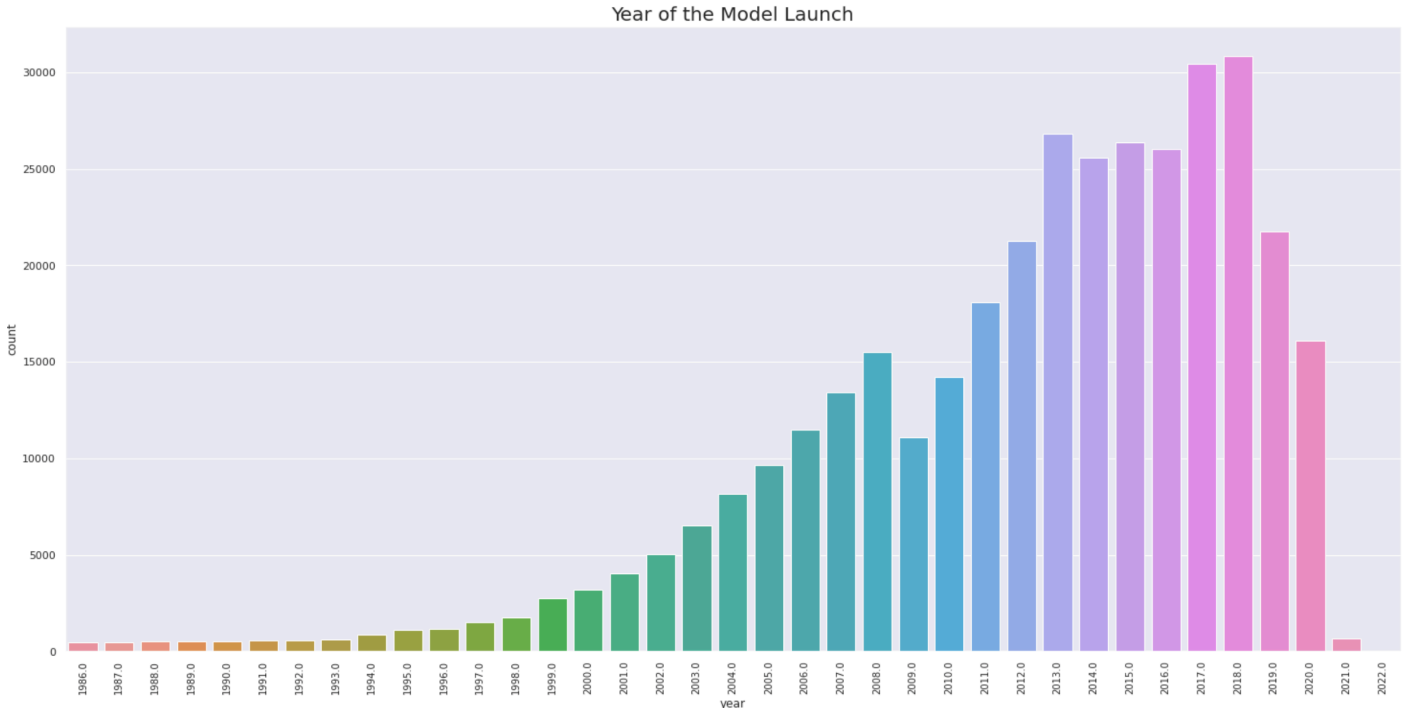
Caption

The Exploratory Data Analysis (EDA)

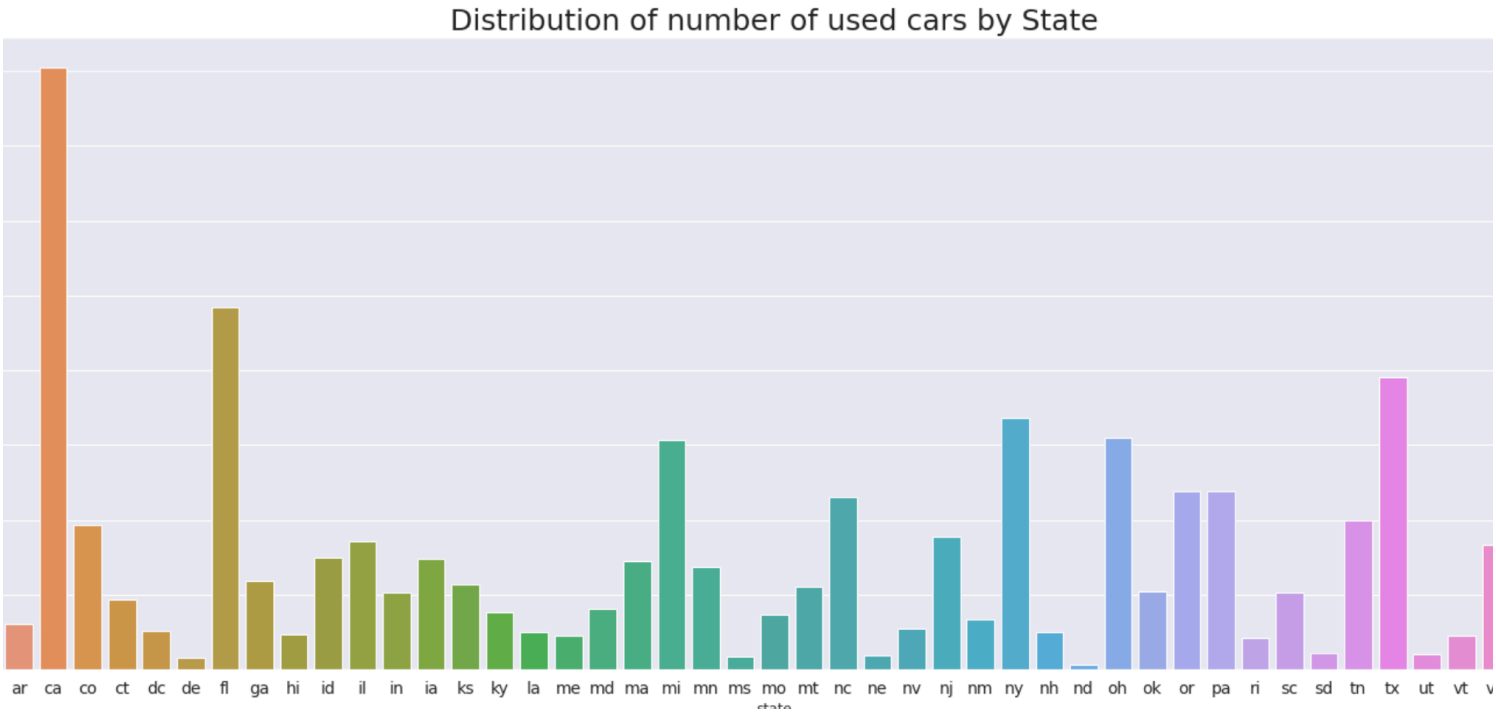
During this process we explore the data. Our goal is to look at the different combinations of features with the help of visual graphs. This will help us to understand our data better and give us some clue about pattern in data. Here are the useful insights:



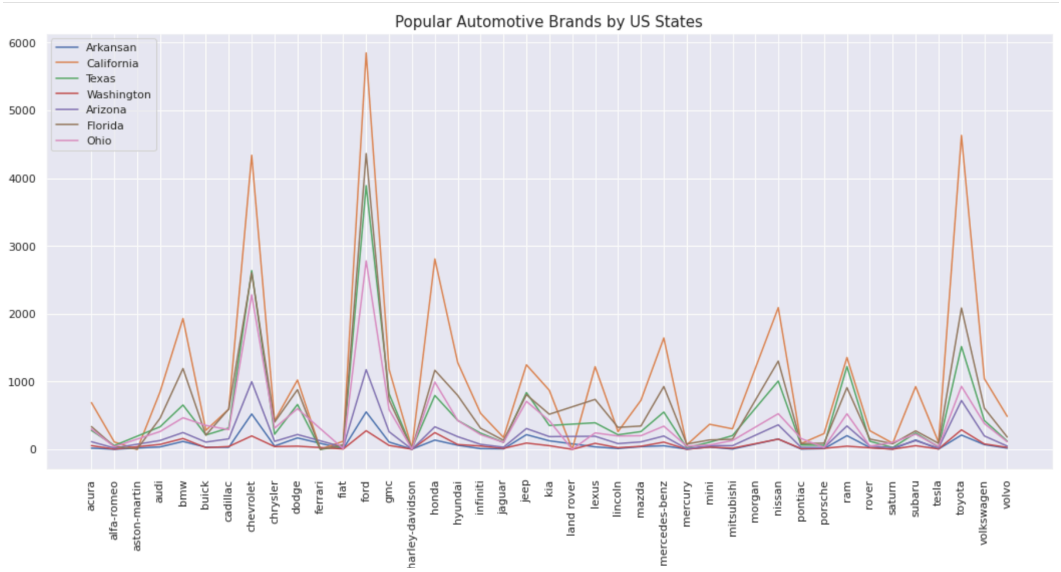
Most popular cars are 4, 6, and 8 Cylinders



Model Launch Year



Cars by state - California is a car state with the most cars in the US



Popular car brands by US States

Machine Learning Models

In this section I applied machine learning models as a framework for the data analysis. The data set is a supervised data which refers to fitting a model of dependent variables to the independent variables, with the goal of accurately predicting the dependent variable for future observations or understanding the relationship between the variables.

In this section, these machine learning models were be applied in order:

* Linear Regression
* Ridge Regression
* Lasso
* K-Nearest Neighbor

Pre-processing the data

Label Encoding. In the dataset, there are 18 predictors. 2 of them are numerical variables while rest of them are categorical. In order to apply machine learning models, we need numeric representation of the features. Therefore, all non-numeric features were transformed into numerical form.

Here are the rest of the steps used:

1) **Train the data.** In this process, 20% of the data was split for the test data and 80% of the data was taken as train data.
2) **Scaling the Data.** While exploring the data during the previous exploration that the data is not normally distributed. Without scaling, the machine learning models will try to disregard coefficients of features that has low values because their impact will be so small compared to the big value features.

Linear Regression

Before applying ridge and lasso, examining linear regression results for initial test. As seen in the code document the performance of the linear regression was not great.

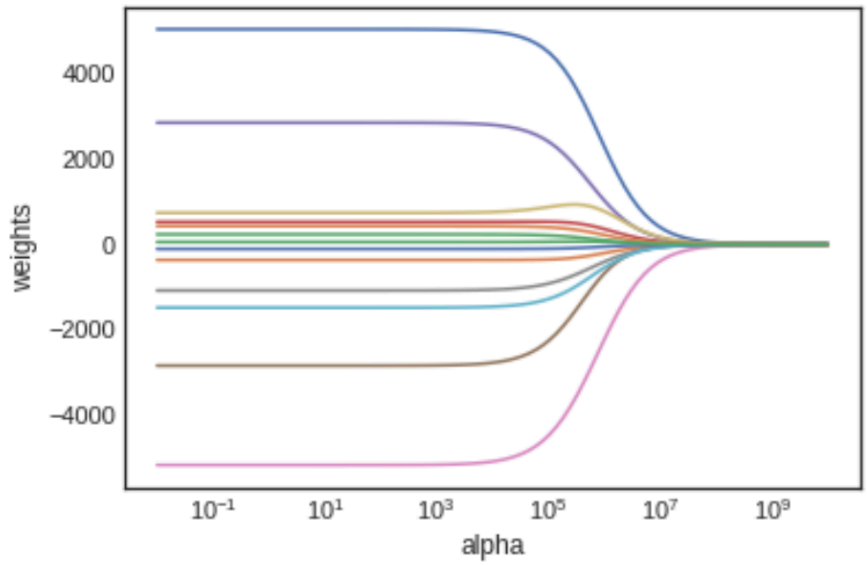
```
-------------Linear Regression-------------
RMSE = 9895.71
Accuracy =  51.083507641643976 %
-------------Ridge Regression--------------
RMSE = 9895.71
```

Table with RMSE

Ridge Regression

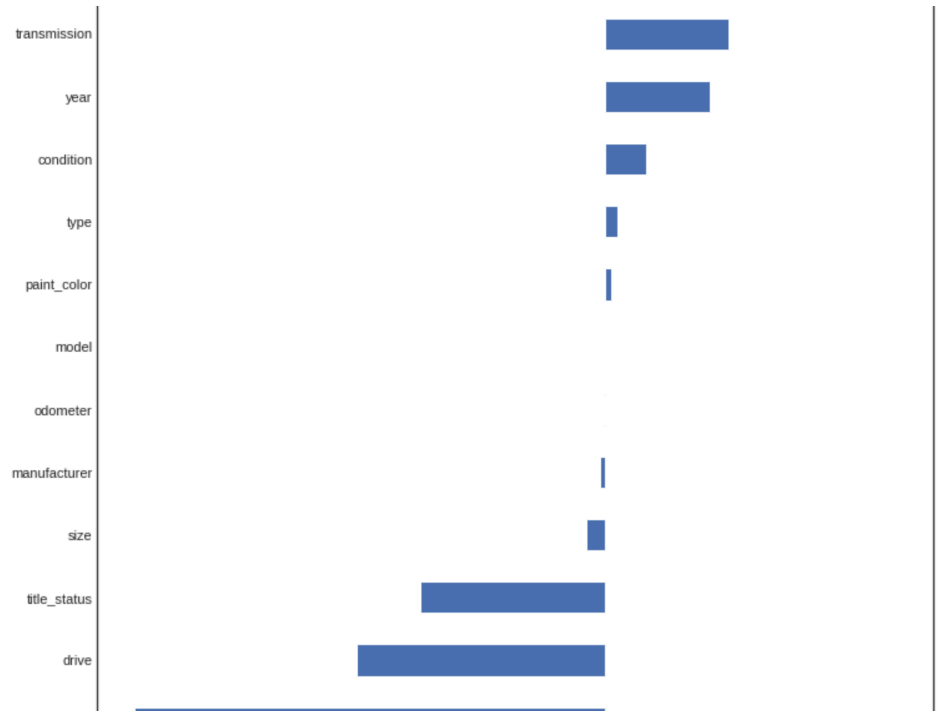
Ordinary least square (OLS) gives unbiased regression coefficients (maximum likelihood estimates “as observed in the data-set”). Ridge regression and lasso allow to regularize (“shrink”) coefficients.

```
Text(0, 0.5, 'weights')
```



Caption

In order to find best alpha value in ridge regression, cross validation was applied. The results are below.



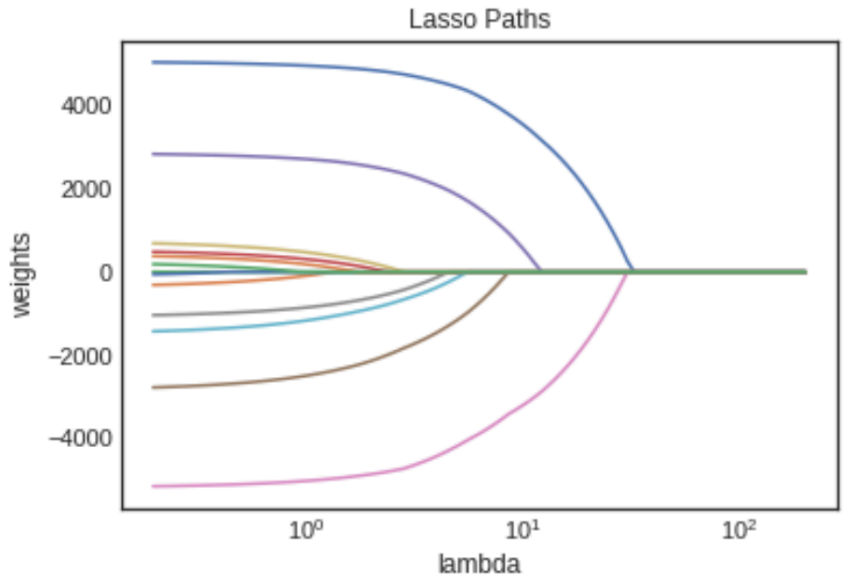
Compared to OLS, the performance of ridge is almost same. Ridge regression suggest that these six variables are the most important ones: year, odometer, fuel, cylinders, title status and drive.

Lasso

Ridge shrinks the coefficients of the variables but does not make them zero. This may be good for certain cases, but it can create a challenge in model interpretation in settings in which the number of variables is quite large. For this dataset, number of variables is not large, so there is no a serious need

for lasso model. However, taking a look at lasso can give us another perspective. And, there is no harm to applying lasso to the dataset other than investing time and effort.

```
<matplotlib.legend.Legend at 0x7f18ec062ad0>
```



Caption

```
training score for alpha =  0.5132435195918412
test score for alpha =  0.5101448807790192
number of features used: for alpha =  12
```

Training and Test Scores

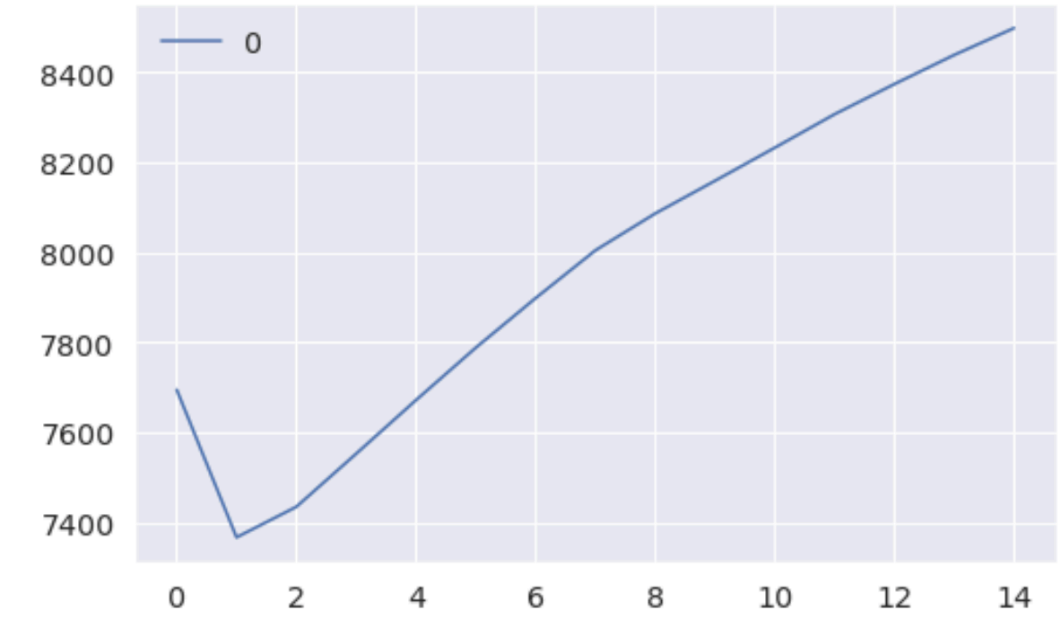
K-nearest Neighbors (KNN)

KNN-classifier can be used when your data set is small enough, so that KNN-Classifier completes running in a shorter time. The KNN algorithm can compete with the most accurate models because it makes highly accurate predictions. Therefore, we can use the KNN algorithm for applications that require a good prediction but do not require a human-readable model. The quality of the

predictions depends on the distance measure. Evaluation of the RMSE values are shown below:

```
RMSE value for k=  1 is: 7695.424317147372
RMSE value for k=  2 is: 7367.400813939839
RMSE value for k=  3 is: 7435.2718809156895
RMSE value for k=  4 is: 7553.182741915963
RMSE value for k=  5 is: 7672.244714175627
RMSE value for k=  6 is: 7788.745904018688
RMSE value for k=  7 is: 7898.851488508709
RMSE value for k=  8 is: 8005.034626749569
RMSE value for k=  9 is: 8086.951550524175
RMSE value for k=  10 is: 8159.6288128156775
RMSE value for k=  11 is: 8233.16978371386
RMSE value for k=  12 is: 8307.570671954567
RMSE value for k=  13 is: 8374.549649999415
RMSE value for k=  14 is: 8439.268463843975
RMSE value for k=  15 is: 8498.914467451295
```

RMSE for K Values



Caption

It is clear that RMSE value is at lowest when k is one.

Conclusion

By using different models, our goal was to get different perspectives and eventually compared their performance. We predicted the price of used cars by using a dataset that has 10 predictors and approximately 359410 rows after cleaning.

We uncovered great insights and explored the data as seen in the graphs above of the data visualizations during the exploratory data analysis. Finally we applied predictive models to predict price of used cars in an order (linear regression, ridge regression, lasso, and KNN). However, this was a relatively small dataset for making a strong inference because number of observations was only 359410.

Gathering more data will yield more robust predictions. Also, we can improve the data cleaning process with the help of more technical information.

As suggestion for further studies, while pre-processing data, instead of using label encoder, I will use one hot encoder method next for better analysis. Thus, all non-numeric features can be converted to nominal data instead of ordinal data.